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Immigrant–Native Wage Inequality across Occupational Sectors in Australia[*]

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Abstract

We investigate wage inequality by migrant status across white collar and blue collar occupations in Australia. We use the reweighting and recentered influence function regression methods proposed by Firpo, Fortin, and Lemieux (2009) to decompose wage differentials across its distribution. Migrants are observed to have a wage advantage, and this wage differential varies over the wage distribution as well as by occupation. Significant wage differentials are found above the median: positive for white collar workers and negative for blue collar workers. Overall, the wage advantage of migrants reflects their superior labour market characteristics, and in particular, their levels of education. A decomposition analysis indicates that migrants receive lower returns for their education. We explore the wage differences by country of origin and find that English language proficiency plays an important role.

Keywords: RIF regressions, wage inequality, occupations, immigration, decomposition, language
JEL Codes: C21, D31, J15, J31

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1. Introduction

The assimilation of immigrants in the labour market is an important measure of success both for the immigrants and for the receiving country. Immigrants typically earn lower wages than natives, and policymakers have been trying to address such immigrant disadvantages in the labour market. One approach to this issue has been to select immigrants with favourable labour market characteristics. The main immigrant-receiving countries, such as Canada, Australia and New Zealand, and some migration streams in the USA and Europe, focus on skilled immigration, which is expected to facilitate the participation and assimilation of migrants in the local labour market. In this paper, we investigate the extent of the earnings differences between migrant and native workers in Australia across different occupations. In to fully understand the nature of these differentials, we examine the wages over the entire distribution. We use the method based on the Recentered Influence Function (RIF) projections developed by Firpo et al. (2009, 2007). The RIF method generates *unconditional* quantile estimates, while the commonly used Quantile Regression (QR) gives *conditional* quantile estimates. Using the RIF unconditional quantile estimates, we decompose the wage gap between migrants and native-born in each occupation at different points of the wage distribution. This enables us to explore the contributions of differences in labour characteristics and differences in labour market returns to the observed gap, over the entire distribution- not just at the means. These decompositions are important for an understanding of the effects and limitations of the policy settings. Immigration policies can influence the composition of immigrant populations by selecting individuals with favourable labour market characteristics, but returns from these characteristics are determined through complex interactions of the economic and structural aspects of local labour market institutions.

The earnings gap between native and migrant workers in Australia has previously been explored by Chiswick and Miller (1985), Beggs and Chapman (1988) and McDonald and Worswick (1999), among others. More recent studies have focused on comparative analysis: Miller and Neo (2003) compared earnings gaps in Australia and the USA, while Antecol *et al.* (2003) compared native–migrant earnings across Australia, Canada and the USA. The common findings can be summarised as follows: (i) migrants in Australia earn less than their native counterparts; (ii) the earnings disadvantage faced by migrants in Australia is small, especially relative to Canada and USA[1] (iii) while there is evidence of labour market assimilation, with migrant earnings increasing with the number of years spent in Australia, the catch-up is very slow (Breunig *et al.*, 2013). Mahuteau and Junankar (2008) find similar assimilation pattern in terms of occupational ladders. Migration to Australia, in terms of both region of origin and skills, changed dramatically during the 1990s.[2] In a recent study, Clarke and Skuterud (2012) compared the economic performances of migrants in Canada and Australia over the period 1986 to 2006. They found that the better labour market conditions in Australia, together with the difference in the source country of migrants, led to a smaller migrant disadvantage than in Canada, in terms of employment and earnings.

The present paper contributes to our understanding of the native–migrant wage differential in Australia in the following ways. We account for the occupational differences between white collar workers and blue collar workers. We focus on skilled and unskilled workers separately considering that Australian immigration policy has become increasingly focused on migrant skill (Islam and Fausten 2008). We employ the recently developed, recentered influence function and decomposition method (Firpo *et al.*, 2007; 2009) to examine the wage gap and the contribution of covariates to the explained and unexplained wage gap across the entire distribution. We also examine the role of English language proficiency in explaining the wage gap among migrants from Non English Speaking countries (NESB). The latter is motivated by our findings that immigrants from NESB and ESB countries do perform differently in labour market. Language proficiency affects both economic and social outcomes of immigrants (see, for example, Chiswick and Miller, 1995). Strong language skills determine the occupations that immigrants could look for, and perform in labour market.

We find that migrants in Australia earn higher wages than natives, overall, though this wage differential varies along the wage distribution, across occupations and countries of origin. Where wage advantages for migrant workers exist, this primarily reflects migrants having higher education levels than natives. When compared with *similarly qualified* native workers, migrants receive lower wages, and thus, lower returns on education. Looking at wage

[1] For example, Miller and Neo (2003) found that, in Australia, migrants earn 12% less than native workers, compared to a 24% gap faced by migrants in the USA.
[2] Skilled migrants formed about 20% of the total immigration intake during the early 1990s, rising to 30% by the mid-1990s, 50% by the late 1990s, and 65% late in the last decade. Similarly, the importance of the UK and the rest of the Europe as the main regions of origin have declined, while Asia has emerged as a major origin for migrants over this time period.

differentials between migrants by origin countries, we find that proficiency in English explains a significant part of the wage gap.

2. Empirical Strategy

To examine the wage inequality between migrants and natives, we ran random effects Generalized Least Squares (GLS) regressions of the natural logarithm of each individual's hourly wage on a migrant indicator dummy, controlling for gender, age, household size, year of observation and geographical location.[3] The results from this regression can be interpreted as capturing the magnitude of the mean unconditional wage inequality between migrants and natives.

The estimation equation is

$$ln\ \mathrm{w}_i = X_i'\beta_1 + M_i\beta_2 + \varepsilon_i\,, \qquad (1)$$

where a subscript i refers to an individual, X is a vector of the characteristics detailed above, β_1 is the corresponding vector of coefficients, M is an migrant dummy variable which is equal to one for migrant, and β_2 measures the wage differential between migrants and natives. Because we have multiple observations for each individual, we cluster standard errors at the person level.[4]

We divide the sample into distinct occupational categories. The occupations are divided into two main categories: white collar workers (consisting of managers and professionals) and blue collar workers (consisting of the remaining occupational groups). A separate analysis of each occupational group allows a comparison of the wage differentials, as well as of the contributions of characteristics such as education, by skill levels.

Education plays an important role in determining labour market earnings, so we also include a vector of variables for education. However, completed education might be a 'noisy' and ethnically-biased measure of individuals' academic skill, given the variation in the quality of

[3] See for example Bjerk (2007) for a justification of the use of the GLS method in a similar context. Bjerk examines the Black–White wage inequality across occupational sectors in the United States, using a panel dataset.
[4] We also cluster standard errors at both the person and survey-year level, since we have repeated person-data. The results are robust to what we present here.

schooling across countries of origin and between migrants and natives. Therefore, the results are likely to understate the actual importance of differences in academic skill. In addition, the education level of an individual can vary depending on her/his ability. Many studies in the context of United States use Armed Forces Qualification Test (AFQT) test scores to measure academic skills or ability. In one such study, Neal and Johnson (1996) show that family background variables such as parental education can explain a significant fraction of AFQT scores. In the absence of any direct measure of cognitive ability, we use parental background as a proxy. We control for both father's and mother's education, in addition to the individual's own education, in order to capture the role of innate ability and academic skills. Parental education is also likely to be a key determinant of educational achievement. For example, Chen (2009) found a significant effect of parental education on children's academic achievements, with father's and mother's educations having different impacts depending on the gender and ability of the children. In the context of immigrants, Card et al. (2000) and Guven and Islam (2013) found a significant intergenerational transmission of level of education and wages. Blau et al. (2013) found that father's education can have a strong effect on the education, fertility and labour supply of second generation female immigrants in the USA. We therefore include controls in this study for both mother's and father's education, in order to account for the underlying abilities and skills of an individual, which may be inherited, transmitted or developed through family channels.

Next, we examine the gap across the entire wage distribution. To account for the fact that the distribution of observable characteristics may be very different across immigrants and natives, as well as across occupation types, we use the decomposition method proposed by Firpo et al. (2009; 2007) (hereafter referred to as the FFL method). This decomposition method is similar in nature to a standard Oaxaca-Blinder decomposition. However, it has the advantage that it allows us to consider the ways in which various characteristics of immigrants and natives affect the distribution of wages at points other than the mean. The method, built on earlier work by DiNardo et al. (1996), provides estimates of the effect of each individual covariate at different parts of the wage distribution. While conditional quintile regressions go beyond the decomposition at the mean, the FFL approach enables unconditional estimates across quantiles, thus capturing the dispersions both 'within' and 'between' groups.

The standard Oaxaca-Blinder decomposition starts with an OLS regression, then decomposes the mean differentials. Following parallel steps, the FFL decomposition starts with the following re-centred influence function (RIF_i) for observation w_i, such that

$$RIF_i = q(\tau) + \frac{[1(w_i \geq q(\tau)) - (1-\tau)]}{f(q(\tau))}, \tag{2}$$

where $f(\,)$ is the density and $1(\,)$ indicates whether the observed wage is at or above the quantile $q(\tau)$. Regressing the RIF_i on characteristics X_i and the migrant dummy as discussed for equation (1) leads to an estimate of $\hat{\beta}$, which represent the estimated partial effects using an unconditional quantile, the marginal effects of the explanatory variables.

The decompositions involve estimating separate RIF regressions for migrant, native and counterfactual wage distributions at chosen quantiles, and performing the usual Blinder-Oaxaca decomposition of each part of the wage gap into differences due to characteristics (the composition effect) and differences in returns (the structure effect). The first stage involves constructing a counterfactual wage distribution that immigrant would have obtained had they received the same returns to their labour market characteristics as native-born population. Thus, the differences between native-born's actual distribution and the counterfactual distribution are attributable to the different characteristics of natives and immigrants (i.e., the "composition effect"), and the differences between immigrants' actual distribution and the counterfactual represent the unexplained migrant earnings gap (i.e., the "structure effect"). In the second stage, composition and wage structure effects are further divided by the separate contribution of each covariate to any distributional statistic of interest, as opposed to just the mean, as in the Oaxaca-Blinder decomposition. This allows us to identify the specific characteristics, differentiated across natives and immigrants, which lead to the nativity earnings gap. The advantages of the RIF method are twofold: first, *unconditional* quantiles are usually of real interest in economic applications; second, this approach allows one to estimate the marginal effects of explanatory variables on the targeted *unconditional* quantiles.

3. Data

We use data from waves 1 to 11 from the Household Income and Labour Dynamics in Australia (HILDA) survey, a longitudinal survey of Australian households. The survey commenced in 2001, and about 15,127 individuals aged 15 and over from 7,683 households are interviewed annually. Immigrants comprise 22% of the HILDA sample, compared to their share (26%) of Australia's total population in 2008 (Australian Bureau of Statistics (ABS), 2010). We restrict our sample to persons aged 20 to 65 years, in order to minimise the impact of labour market entries and exits. Migrants are defined based on their country of birth: those born overseas are classified as migrants and Australian-born individuals are classified as natives. In order to capture the wage inequality across occupations, workers are divided into two groups: managers and professionals are grouped together under the heading of white collar workers, while blue collar workers consist of technicians and trades workers, community and personal service workers, clerical and administrative workers, sales workers, machinery operators and drivers, and labourers. For the analysis, we pooled the data from all waves together. The empirical strategy of employing pooled data and random effects estimation allows us to exploit more variation than is possible with either the panel data or cross sectional data approaches, particularly as the sample is restricted to individuals aged 20 to 65.[5]

INSERT TABLE 1 HERE

Descriptive statistics and the differences between natives and migrants, along with the significance of such differences using the *t*-test, are reported in Table 1. Natives and migrants differ in terms of their labour market characteristics. On average, migrants are older, more experienced, and more likely to be married than natives. In contrast to widely held perceptions, migrants earn higher weekly wages than natives, and work fewer hours per week, on average. Considering hourly wages, taking into account weekly wages and hours worked, migrants still maintain a wage advantage over natives. Education plays an important role in determining wages. Across the population, migrants are better qualified than natives, a higher proportion of migrants hold either a graduate or postgraduate qualification compared to natives and a lower proportion of migrants did not complete Year 12. Wages differ across occupations. The means reported in Table 1 indicate that there are small, but significant, differences between the occupational distributions of native and migrant workers.[6] Compared to natives, a higher proportion of migrants are in white collar occupations and a lower proportion are in blue collar occupations. Kernel density estimates for logged hourly wages are plotted in Figure 1 in order to illustrate the wage distributions of native and migrants in

[5] See Breunig et al. (2013) for an analysis of the immigrant wage gap using panel data approach.
[6] See Parasnis (2006) for a detailed analysis of migrant segregation in the Australian labour market.

the two occupational groups. Consistent with the mean differences noted above, there is no evidence of a migrant disadvantage in the wage distributions.

INSERT FIGURE1 HERE

4. Estimation Results

4.1 Results: Random Effect GLS

INSERT TABLE 2 HERE

Table 2 reports the random effect GLS estimates for all workers. Consistent with the earlier discussion of the unconditional wage gap, migrant earnings are higher than native earnings when we do not control for any demographic variables (column 1). This observed migrant wage advantage reflects the favourable characteristics of migrant workers: the wage advantage becomes insignificant once we control for age, and negative when we control for education. Contrary to our expectation, controlling for parental education does not have much effect on the results. The remaining variables are of the expected signs: wages increase with age, are lower for female workers, and increase with education levels. The results underline the comparatively better education profile of migrant workers. Analysing the wage differences by occupational groups (Table 3 for white collar and Table 4 for blue collar workers) provides further insights into this finding.

INSERT TABLE 3 HERE

INSERT TABLE 4 HERE

The migrant wage advantage primarily reflects migrants' higher education levels. However, a migrant with the same educational level as a native worker earns less in both white collar and blue collar occupations, though the difference is not statistically significant for white collar workers. While we cannot draw any definitive conclusions, the results indicate that parental education (or an individual's ability) plays a role, to some extent, for migrant workers in white collar occupations. Column 4 in Table 3 shows that the coefficient becomes more negative when we control for ability (parental education). However, the difference between the coefficients of the migrant variable in columns 3 and 4 is not statistically significant, and therefore the results are only suggestive.

INSERT TABLE 5 HERE

Differences across migrant countries of origin are well documented in the Australian literature. The top panel in Table 5 reports the results by origin countries, disaggregating migrants into those originating from English-speaking countries (ESB) and those from non-English-speaking countries (NESB). Regardless of their occupation, ESB migrants earn higher wages and NESB migrants earn lower wages than their native counterparts, leading to about a 10% wage gap between ESB and NESB migrants. This finding is the latest addition to the literature on the well-documented difference between these two migrant groups. Various studies have discussed the possible effects of different characteristics in explaining the labour market disadvantage of NESB migrants, particularly the effect of English language proficiency. Chiswick and Miller (1995) and Dustmann and Fabbri (2003) documented the link between language and earnings; however, there has been little empirical evaluation of the factors which contribute to the ESB–NESB wage differential. One reason for this could be the lack of data. Ideally, a further disaggregation of migrants by origin countries and a richer dataset on migrants would enable us to differentiate between the effects of migrant characteristics, origin country institutions and language in determining Australian labour market outcomes. Unfortunately, this is hampered by the lack of availability of data which are suitable for empirical analysis. However, the questions on language in HILDA allow us to shed further light on the wage disadvantage of NESB migrants by including English language proficiency explicitly.

The second panel of Table 5 reports the estimates for the sample of NESB migrants, including English language proficiency (*english*) as an independent variable. The variable is constructed from individuals' self-reported English speaking ability, increasing from 0 (not well at all) to 3 (very well). The question was only asked of migrants who reported speaking a language other than English at home, and hence, the sample is restricted to NESB migrants. The reported mean value of *english* is 2.327, with 55% reporting that they speak well or very well. English language proficiency has a significant positive effect on wages. A one-unit increase in English ability leads to a 10% increase in wages for white collar workers, while the corresponding increase for blue collar workers is 6%. Given that ESB migrants are expected to speak English very well, our results suggest that the level of proficiency in English explains almost all of the wage differences between ESB and NESB migrants. For NESB migrants, English language ability can also be considered as a proxy for unobserved ability and productivity (omitted variable problem). Thus, the coefficient of English language skills could reflect the effect of both language and unobserved ability, and thus, the observed magnitude of the English coefficient could be interpreted as the gross effects of language skills in Australia.

Note that, while language skills can explain the observed differences in wages between ESB and NESB migrant workers, we cannot rule out an explanation based on stereotyping, such as possible discrimination between native-born and migrant workers, or between NESB and ESB migrants. The decomposition analysis presented below sheds further light on the presence of such factors.

Although we account for occupational settings, the distribution of migrant and native employment differs across industries. Migrants are more likely to be employed in manufacturing, IT, financial and professional related industries, while they are less likely to be in agriculture, hospitality and trades. We address this issue by including industries as additional controls in our estimations; the results are documented in the Appendix (Table A1). These results support our earlier findings of a statistically insignificant wage disadvantage for migrants in white collar occupations and statistically significantly lower wages for blue collar migrants. Thus, our main findings are not driven by the wage structure of industries.

4.2 Results: RIF Regression

INSERT TABLE 6 HERE

The results from RIF regressions are tabulated in Table 6. All estimations include a full set of control variables. The migrant–native wage difference varies along the distribution and across the two occupational classifications. In white collar occupations, migrants have both lower wages (below the median) and higher wages (above the median). A 2% wage disadvantage is observed at the 25th percentile, while at the 75th percentile, migrants have a 2% wage advantage over their native-born counterparts. The regression results are the opposite for blue collar occupations: above the median migrants earn lower wages; specifically, at the 75th percentile of the wage distribution, blue collar immigrants in Australia receive 3% lower wages than native workers.

4.3 Results: FFL Decomposition

INSERT TABLE 7 HERE

We further decompose the observed wage differential into the composition effect and the wage structure effect (Table 7). The first row of the table reports the difference between the log of hourly wages of migrants and native-born workers at different quantiles, with positive values reflecting higher migrant wages.[7] The wage difference in favour of migrants increases over the quantiles but there are differences across occupations. While white collar migrants have 4% higher wages at the 10th percentile, increasing to almost 13% at the 90th percentile, blue collar workers have, at most, 3% higher wages than their native counterparts.

The composition effect captures the contribution of characteristics to the overall wage differential. The positive sign of the composition effect (tabulated in the second panel in Table 7) indicates that the migrant wage advantage arises as a result of migrant workers' better labour market characteristics. The age and gender profile of immigrants works in their favour. Again, education is an important contributor to the migrant wage advantage. In particular, postgraduate degrees contribute significantly to migrant wages in white collar occupations. For blue collar workers as well, postgraduate and graduate education contributes to higher migrant wages (except at the 90th quantile).

Overall, the wage structure effect is negative, indicating that if natives received the same returns to their characteristics as migrant workers, their wages would be lower, particularly at the 50th and 75th quantiles. However, we do not find a persistent negative effect when looking at the results by occupation. Given the focus on skills in the migration and labour markets, the returns to education are of particular interest. Regardless of their occupation and education level, we find that migrants receive lower returns to their education. Again, the only exception is for the blue collar workers at the top of the wage distribution.

5. Discussion of Results

Given that the aim of the paper is to analyse native–migrant wage differentials, our empirical estimates reflect labour market outcomes for employed workers. Thus, they are conditional on participation and unemployment. However, we note that natives and migrants differ in

[7] The wage differential is calculated as (exp(log points difference) – 1) × 100).

terms of their probabilities of participation and employment. Migrants have higher probabilities of unemployment: 3.6% of migrants are unemployed, compared to 3% of natives. In addition, 24.7% of migrants do not participate in the labour force, compared to 19.5% of natives. If these differences in labour force participation are driven mainly by migrants with low returns in the labour market, our estimates underestimate the underlying extent of the migrant wage disadvantage.

The issue of migrant selection may arise even before migrants enter the Australian labour market; that is, immigrants may self-select to join the labour market in countries which are booming (Friedberg and Hunt, 1995), and where their skills are in demand. As noted by Borjas (1987), immigrants are probably not a random subset of the source countries' workforces. We would expect those who immigrate to have higher expected levels of earnings in Australia than in their country of origin, and vice versa for those who do not immigrate. Typically, immigrants are ambitious, aggressive and entrepreneurial. Skilled migrants in particular move across international boundaries in order to exploit the economic opportunities that are accessible to them. It is also likely that the Australian government bases its immigration policy on past immigration rates and/or domestic labour market conditions. In a recent study, Breunig et al. (2013) found evidence that the more recent cohorts of immigrants to Australia experience smaller wage gaps than earlier cohorts. Our results also point to a positive selection of migrants on unobservables.

We find that education explains the migrant wage advantage in white collar jobs; controlling for education and parental background, there are no significant differences between native and migrant workers. In blue collar occupations, however, migrants have lower wages after accounting for education and ability. Bjerk (2007) shows that this pattern of wage inequality across occupational sectors is consistent with both preference-based and statistical discrimination. Preference-based discrimination is likely to persist in blue collar occupations but not in white collar occupations. The importance of skills for productivity in white collar occupations results in much higher costs for any firms in this sector that exercise discriminatory preferences. The direct link between skills and productivity is weaker in the blue collar sector, and hence, the cost of engaging in discrimination is lower. Similarly, given this importance of skills in white collar jobs, these firms are likely to spend more resources in gauging worker productivity directly, instead of merely using migrant status as a signal. Hence, it is likely that lower wages due to statistical discrimination will not be observed in white collar jobs, but will continue to prevail in blue collar jobs. Apart from discrimination, these differences in wage inequality between the two sectors can arise from an omitted variables bias and measurement errors. The negative coefficient on the migrant variable may be due to unobserved characteristics which are correlated with migrant status. However, we observe that the coefficient differs across occupations within white and blue collar occupations. As was pointed out by Bjerk (2007), omitted variables in such cases tend to exhibit differential distributions by worker type (native–migrant) and/or occupational group (white collar–blue collar).

The empirical strategy of pooling the data across waves enables us to exploit the variation in the data. However, in order to investigate differences at particular points in time, we estimate the model separately for waves 1, 6 and 11. The results are documented in the Appendix (Tables A2, A3 and A4, for waves 1, 6 and 11, respectively). While the results confirm the findings regarding the migrant disadvantage, the coefficients on the migrant dummy are generally statistically insignificant when controlling for education.

While we do find evidence of lower returns to education for migrants, we do not find any systematic negative structural effects across occupations within white collar and blue collar occupations. Given the results underlining the importance of language proficiency, lower returns on education may reflect the differences in the language of instruction and the quality of the institutions at which the education was obtained. There could also be additional factors which inhibit the transfer of skills between countries, and migrants could face disadvantages in dimensions other than wages, such as problems of over-skilling, and even of securing employment in the first instance.

6. Conclusion

We investigate the migrant–native wage inequality in two important dimensions, between white collar and blue collar occupations and along the wage distribution. Furthermore, we employ the recent advances in the decomposition literature to explore the contributions of characteristics and returns to characteristics to the overall wage differential. Our results show that migrants in Australia have a wage advantage relative to natives, which reflects their more favourable labour market characteristics. The wage differential varies by occupation and over the wage distribution. White collar migrants experience a positive wage differential at the higher end of the wage distribution, while blue collar migrants have a negative wage differential at the higher end.

The analysis underlines the importance of education in determining the migrant wage advantage. All estimations, as well as the decomposition analysis, indicate that the higher wages are a reflection of migrants' better education profile. However, migrants receive lower returns on their education. We confirm that the wage differential varies by the country of origin. Our results also highlight the role of English language proficiency, in explaining ESB–NESB wage differences. Australia's migration policy is aimed at the selection of migrants with better labour market characteristics; in terms of age, education and language requirements. These seem to reduce the wage disadvantage faced by migrants.

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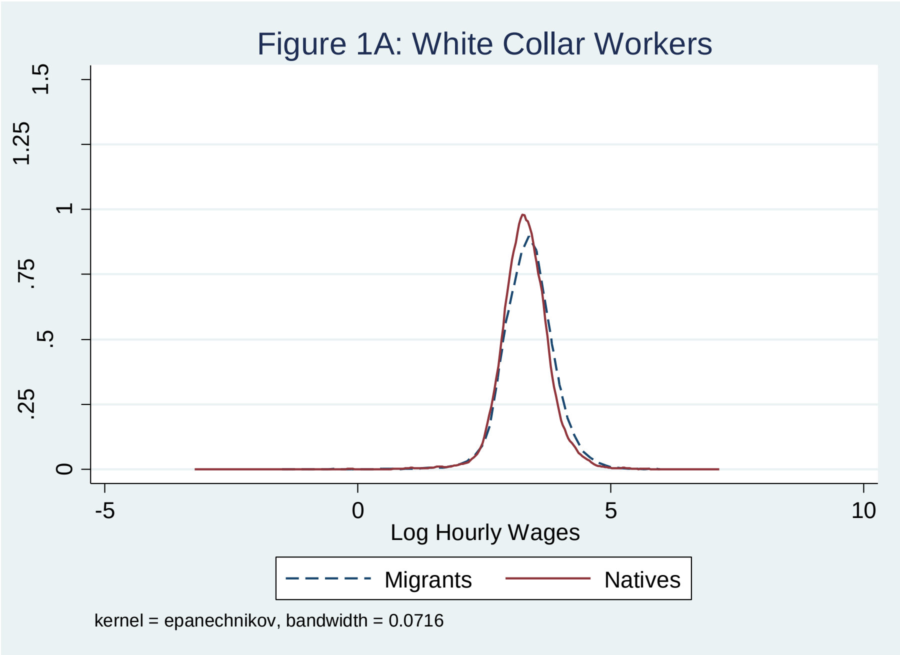
Figure 1: Hourly Wages (kernel density estimates)



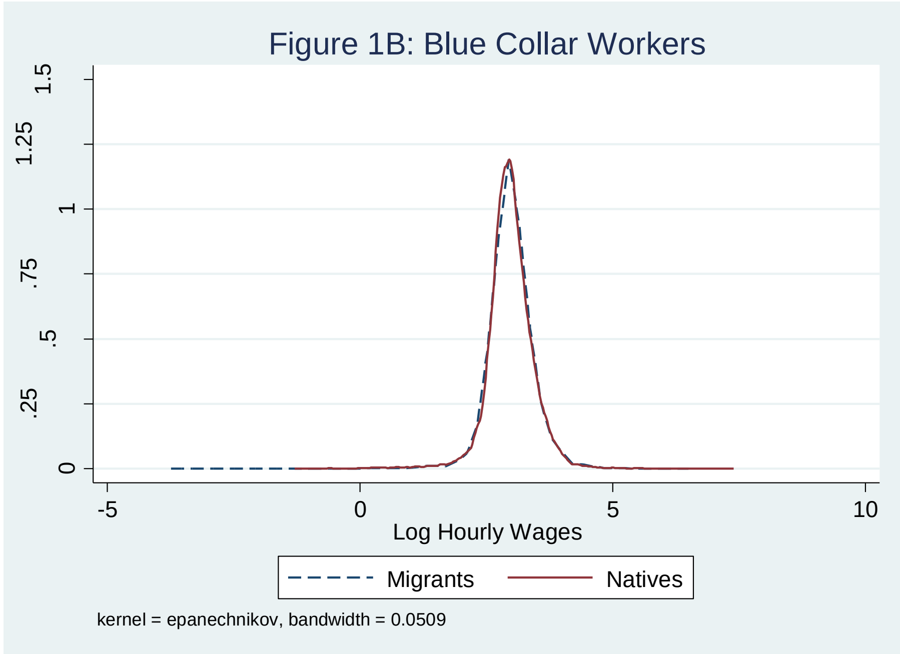


Table 1: Descriptive Statistics

Variable	Natives		Migrants		Difference
	Mean	Std Dev	Mean	Std Dev	
Age	42.305	(18.508)	49.363	(16.996)	–7.058***
Female	0.528	(0.499)	0.522	(0.499)	0.006**
Married	0.594	(0.491)	0.706	(0.455)	–0.112***
Experience	25.609	(18.485)	31.347	(17.123)	–5.739***
Log weekly wage	6.453	(0.893)	6.614	(0.797)	–0.162***
Weekly hours	23.986	(21.753)	21.576	(21.647)	2.409***
Log hourly wage	3.007	(0.574)	3.105	(0.576)	–0.098***
Education					
Postgraduate	0.026	(0.159)	0.056	(0.231)	–0.030***
Bachelor degree/diploma	0.239	(0.426)	0.304	(0.460)	–0.065***
Vocational certificates	0.215	(0.411)	0.197	(0.398)	0.018***
Year 12	0.149	(0.357)	0.159	(0.366)	–0.010***
Year 11 and below	0.370	(0.483)	0.282	(0.450)	0.088***
Occupation					
Blue Collar	0.649	(0.477)	0.594	(0.491)	0.055***
White Collar	0.351	(0.002)	0.406	(0.491)	–0.055***

Notes: The last column reports the difference between natives and migrants, with superscripts denoting the significance of a *t*-test of the differences. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Random Effect GLS Regressions for All Workers

Log Hourly Wages	(1)	(2)	(3)	(4)
Migrant	0.044***	0.010	–0.029***	–0.028***
	(0.009)	(0.008)	(0.008)	(0.009)
Age		0.046***	0.041***	0.044***
		(0.002)	(0.002)	(0.002)
Female		–0.123***	–0.138***	–0.133***
		(0.007)	(0.006)	(0.007)
Postgraduate			0.430***	0.392***
			(0.015)	(0.016)
Bachelor degree/diploma			0.293***	0.265***
			(0.009)	(0.011)
Vocational certificates			0.089***	0.077***
			(0.009)	(0.011)
Year 12			0.121***	0.101***
			(0.011)	(0.013)
Household size		–0.004**	–0.001	–0.002
		(0.002)	(0.002)	(0.002)
Control for year	Yes	Yes	Yes	Yes
Control for state	Yes	Yes	Yes	Yes
Control for parents' schooling	No	No	No	Yes
Observations	67,050	67,050	67,050	55,897
Number of individuals	14,541	14,541	14,541	11,016

Notes: The table reports coefficients from random effect GLS. The regressions also include the square of age. Standard errors clustered at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Random Effect GLS Regressions for White Collar Workers

Log Hourly Wages	(1)	(2)	(3)	(4)
Migrant	0.065***	0.024*	–0.004	–0.006
	(0.01)	(0.012)	(0.012)	(0.013)
Age		0.053***	0.051***	0.052***
		(0.003)	(0.003)	(0.003)
Female		–0.105***	–0.124***	–0.127***
		(0.010)	(0.010)	(0.011)
Postgraduate			0.361***	0.323***
			(0.022)	(0.025)
Bachelor degree/diploma			0.295***	0.264***
			(0.019)	(0.021)
Vocational certificates			0.064***	0.043*
			(0.021)	(0.023)
Year 12			0.185***	0.156***
			(0.023)	(0.026)
Household size		–0.001	0.001	0.000
		(0.00282)	(0.003)	(0.003)
Control for year	Yes	Yes	Yes	Yes
Control for state	Yes	Yes	Yes	Yes
Control for parents' schooling	No	No	No	Yes
Observations	24,941	24,941	24,941	22,310
Number of individuals	6,440	6,440	6,440	5,377

Notes: The table reports coefficients from random effect GLS. The regressions also include the square of age. Standard errors clustered at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Random Effect GLS Regressions for Blue Collar Workers

Log Hourly Wages	(1)	(2)	(3)	(4)
Migrant	0.019**	–0.004	–0.029***	–0.029***
	(0.009)	(0.009)	(0.009)	(0.010)
Age		0.035***	0.033***	0.036***
		(0.002)	(0.002)	(0.002)
Female		–0.131***	–0.133***	–0.127***
		(0.007)	(0.007)	(0.008)
Postgraduate			0.353***	0.349***
			(0.028)	(0.031)
Bachelor degree/diploma			0.176***	0.160***
			(0.011)	(0.012)
Vocational certificates			0.084***	0.076***
			(0.009)	(0.011)
Year 12			0.074***	0.062***
			(0.011)	(0.012)
Household size		–0.004**	–0.002	–0.004*
		(0.002)	(0.002)	(0.002)
Control for year	Yes	Yes	Yes	Yes
Control for state	Yes	Yes	Yes	Yes
Control for parents' schooling	No	No	No	Yes
Observations	42,070	42,070	42,070	33,558
Number of individuals	11,186	11,186	11,186	8,305

N
otes: The table reports coefficients from random effect GLS. The regressions also include the square of age. Standard errors clustered at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Random Effect GLS Regressions by Country of Origin

Log Hourly Wages	All workers	White Collar	Blue Collar
ESB	0.028**	0.034*	0.013
	(0.013)	(0.017)	(0.015)
NESB	–0.078***	–0.048***	–0.065***
	(0.012)	(0.018)	(0.013)
Observations	55,897	22,310	33,558
No of individuals	11,016	5,377	8,305
NESB workers			
English	0.082***	0.102***	0.062***
	(0.014)	(0.032)	(0.015)
Observations	3,911	1,501	2,408
No of individuals	1,016	452	722
Control for year	Yes	Yes	Yes
Control for state	Yes	Yes	Yes
Control for parents' schooling	Yes	Yes	Yes

Notes: The table reports coefficients from random effect GLS. The regressions include controls for age, age squared, gender, education level, household size, year, state and parents' schooling. Standard errors clustered at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Re-centred Wage Regressions

Log Hourly Wages	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
All workers					
Migrant	–0.009	–0.009*	–0.028***	–0.033***	–0.006
	(0.007)	(0.005)	(0.005)	(0.006)	(0.010)
Observations	55,897	55,897	55,897	55,897	55,897
R-squared	0.077	0.165	0.221	0.196	0.109
White Collar Workers					
Migrant	0.001	–0.019**	0.004	0.021**	0.048***
	(0.012)	(0.008)	(0.008)	(0.009)	(0.016)
Observations	22,310	22,310	22,310	22,310	22,310
R-squared	0.087	0.164	0.208	0.167	0.086
Blue Collar Workers					
migrant	–0.002	0.004	–0.002	–0.031***	–0.074***
	(0.009)	(0.006)	(0.005)	(0.008)	(0.012)
Observations	33,558	33,558	33,558	33,558	33,558
R-squared	0.059	0.138	0.165	0.139	0.080
Control for year	Yes	Yes	Yes	Yes	Yes
Control for state	Yes	Yes	Yes	Yes	Yes
Control for parents' schooling	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficients from random effect GLS. The regressions include controls for age, age squared, gender, education level, household size, year, state and parents' schooling. The standard errors are clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: FFL Decomposition of the Migrant–Native Wage Gap

Log Hourly Wages	All Workers					White Collar Workers					Blue Collar Workers				
	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
Difference (Migrant–Native)	0.021	0.033	0.037	0.050	0.093	0.041	0.050	0.081	0.090	0.127	0.001	0.018	0.024	0.007	0.030
Composition Effect	0.024	0.040	0.072	0.091	0.097	0.051	0.066	0.069	0.076	0.088	–0.003	0.007	0.024	0.044	–0.024
Age	0.145	0.135	0.162	0.164	0.107	0.174	0.179	0.168	0.132	0.096	0.137	0.105	0.118	0.141	–0.103
Female	0.000	0.000	0.001	0.001	0.001	0.003	0.004	0.006	0.008	0.012	–0.001	–0.002	–0.003	–0.004	0.006
postgraduate	0.011	0.015	0.023	0.030	0.030	0.032	0.030	0.025	0.024	0.024	0.003	0.004	0.006	0.012	–0.006
Bachelor degree/diploma	0.016	0.019	0.026	0.027	0.022	–0.007	–0.005	–0.004	–0.003	–0.003	0.010	0.011	0.016	0.023	–0.017
Vocational certificates	–0.007	–0.006	–0.007	–0.005	–0.002	–0.004	–0.003	–0.001	0.000	0.001	–0.005	–0.005	–0.006	–0.008	0.004
Year 12	0.000	0.000	0.000	0.000	0.000	–0.001	–0.001	–0.001	–0.001	–0.001	0.000	0.001	0.001	0.001	0.000
Structure Effect	–0.003	–0.007	–0.036	–0.041	–0.004	–0.011	–0.017	0.012	0.014	0.038	0.003	0.011	0.000	–0.036	0.054
Age	–0.373	–0.285	–0.430	–0.379	0.452	0.077	0.096	–0.510	0.044	0.759	–0.523	–0.245	–0.552	–0.577	0.413
Female	–0.009	–0.007	0.010	0.018	0.006	–0.013	0.011	0.020	0.016	0.023	–0.005	–0.008	0.005	0.016	–0.006
Postgraduate	–0.007	–0.007	–0.010	–0.011	–0.009	–0.060	–0.027	–0.016	–0.014	–0.010	–0.001	–0.001	–0.003	–0.011	0.006
Bachelor degree/diploma	–0.023	–0.023	–0.030	–0.014	0.003	–0.180	–0.053	–0.020	–0.008	0.003	–0.008	–0.006	–0.018	–0.033	0.020
Vocational certificates	–0.011	–0.010	–0.020	–0.016	–0.012	–0.020	–0.016	–0.010	–0.004	–0.004	–0.011	–0.009	–0.015	–0.026	0.018
Year 12	–0.011	–0.011	–0.015	–0.011	–0.007	–0.017	–0.016	–0.008	–0.001	–0.003	–0.009	–0.006	–0.012	–0.017	0.019

Notes: Base Category: year (wave 1), father's education (did not complete primary school), mother's education (did not complete primary school), state (NSW). Controls for parents' education include a separate set of dummies for different levels of schooling (e.g., no education, primary school, secondary school, bachelor degree, etc.). Estimations include age squared and household size as controls.

Appendix

Table A1: Random Effect GLS Regressions: Controlling for Industries

Log Hourly Wages	All Workers	White Collar	Blue Collar
Migrant	–0.025***	–0.011	–0.023**
	(0.009)	(0.013)	(0.010)
Age	0.040***	0.050***	0.032***
	(0.002)	(0.003)	(0.002)
Female	–0.123***	–0.127***	–0.100***
	(0.007)	(0.011)	(0.008)
Postgraduate	0.381***	0.304***	0.335***
	(0.016)	(0.025)	(0.031)
Bachelor degree/diploma	0.251***	0.241***	0.154***
	(0.012)	(0.022)	(0.012)
Vocational certificates	0.072***	0.039*	0.072***
	(0.010)	(0.023)	(0.010)
Year 12	0.102***	0.145***	0.064***
	(0.012)	(0.026)	(0.012)
Household size	–0.001	0.001	–0.003
	(0.002)	(0.003)	(0.002)
Control for year	Yes	Yes	Yes
Control for state	Yes	Yes	Yes
Control for parents' schooling	Yes	Yes	Yes
Control for industries	Yes	Yes	Yes
Observations	55,584	22,170	33,389
Number of individuals	10,981	5,357	8,278

Notes: The table reports coefficients from random effect GLS. The regressions also include the square of age. Standard errors clustered at individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2: Random Effect GLS Regressions, Wave 1

Log Hourly Wages	All Workers	White Collar Workers	Blue Collar Workers
Migrant	–0.013	–0.039	0.023**
	(0.009)	(0.023)	(0.008)
Age	0.045***	0.061***	0.031**
	(0.006)	(0.005)	(0.009)
Female	–0.116***	–0.134***	–0.099***
	(0.014)	(0.012)	(0.020)
Postgraduate	0.399***	0.243***	0.380***
	(0.027)	(0.041)	(0.038)
Bachelor degree/diploma	0.303***	0.222***	0.162***
	(0.018)	(0.035)	(0.027)
Vocational certificates	0.047*	0.016	0.044
	(0.023)	(0.061)	(0.027)
Year 12	0.109***	0.135***	0.056
	(0.023)	(0.036)	(0.032)
Household size	0.0015	–0.002	0.001
	(0.004)	(0.008)	(0.006)
Control for state	Yes	Yes	Yes
Control for parents schooling	Yes	Yes	Yes
Control for industries	Yes	Yes	Yes
Observations	4,110	1,691	2,415
Number of individuals	0.143	0.108	0.055

Notes: The table reports coefficients from random effect GLS. The regressions also include the square of age. The standard errors are clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Random Effect GLS Regressions, Wave 6

Log Hourly Wages	All Workers	White Collar Workers	Blue Collar Workers
Migrant	–0.015	0.001	–0.011
	(0.013)	(0.015)	(0.010)
Age	0.039***	0.056***	0.029***
	(0.004)	(0.010)	(0.003)
Female	–0.124***	–0.116***	–0.123***
	(0.014)	(0.024)	(0.018)
Postgraduate	0.487***	0.329***	0.496***
	(0.022)	(0.071)	(0.066)
Bachelor degree/diploma	0.318***	0.269***	0.154***
	(0.008)	(0.051)	(0.013)
Vocational certificates	0.095***	0.079	0.082**
	(0.023)	(0.052)	(0.031)
Year 12	0.121***	0.124**	0.084***
	(0.011)	(0.050)	(0.019)
Household size	0.007**	0.001	0.008**
	(0.002)	(0.003)	(0.003)
Control for state	Yes	Yes	Yes
Control for parents' schooling	Yes	Yes	Yes
Control for industries	Yes	Yes	Yes
Observations	5,191	2,022	3,169
Number of individuals	0.175	0.144	0.088

Notes: The table reports coefficients from random effect GLS. The regressions also include the square of age. The standard errors are clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Random Effect GLS Regressions, Wave 11

Log Hourly Wages	All Workers	White Collar Workers	Blue Collar Workers
Migrant	–0.039**	–0.015	–0.024
	(0.016)	(0.013)	(0.025)
Age	0.041***	0.058***	0.030***
	(0.007)	(0.009)	(0.006)
Female	–0.152***	–0.160***	–0.128***
	(0.019)	(0.025)	(0.017)
Postgraduate	0.502***	0.361***	0.346***
	(0.024)	(0.046)	(0.075)
Bachelor degree/diploma	0.340***	0.302***	0.153***
	(0.014)	(0.049)	(0.017)
Vocational certificates	0.117***	0.065	0.117***
	(0.013)	(0.060)	(0.013)
Year 12	0.123***	0.171*	0.069**
	(0.011)	(0.074)	(0.027)
Household size	–0.000	–0.000	0.000
	(0.004)	(0.006)	(0.0040)
Control for state	Yes	Yes	Yes
Control for parents' schooling	Yes	Yes	Yes
Control for industries	Yes	Yes	Yes
Observations	7,155	2,887	4,260
Number of individuals	0.185	0.167	0.083

Notes: The table reports coefficients from random effect GLS. The regressions also include the square of age. The standard errors are clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.